Local Knowledge Spillovers

in the

Taiwanese Electronics Industry

Tor Winston*
February 2003

Abstract
This paper examines the hypothesis put forward by Alfred Marshall that geographic proximity facilitates the spread of knowledge among firms. Previous empirical research using data from developing countries has focused on foreign direct investment and export experience as specific sources of knowledge spillovers. The empirical model uses an index measure of total factor productivity (TFP) to measure the knowledge that can potentially spillover from one firm to another. Using micro panel data from the Taiwanese electronics industry in 1986, 1991, and 1996, measures of knowledge stocks are constructed for each of ten 3-digit industries in each of 21 locations. Controlling for endogenous firm exit and the productivity effects of location-specific characteristics, a firm's future TFP is estimated as a function of its local industry-specific knowledge. The results indicate that local knowledge spillovers from high productivity firms have an economically and statistically significant positive effect on a firm's future productivity. In addition, the findings indicate that lower productivity firms benefit most from their proximity to high productivity neighbors. These findings are consistent with the hypothesis that physical proximity between firms facilitates the flow of knowledge among them.

*Economist, Antitrust Division, U.S. Department of Justice, Economic Analysis Group, 600 E Street, NW, Suite 10000, Washington DC 20530. This research was conducted as part of my dissertation at The Pennsylvania State University. I would like to thank Bee Yan Aw and Mark J. Roberts for their many helpful comments and suggestions. The views expressed here are not purported to be those of the U.S. Department of Justice.

1 Introduction

The Taiwanese electronics industry has much in common with industries where geography is thought to play an important role in economic development and productivity growth. Several researchers have drawn attention to the importance of the physical agglomeration of firms to the success of industries in Silicon Valley and Industrial Districts of Northern Italy. Silicon Valley is frequently described as having a culture of competition, collaboration, and risk taking where small firms temporarily band together to develop and produce products for a rapidly changing market. Similarly, the success of the Italian Industrial Districts (or local production economies) is often attributed to the interdependence and subcontracting between specialized small and medium sized enterprises (SMEs).[1] The Taiwanese electronics industry is both rapidly changing, like the Silicon Valley industries, and highly decentralized, like the Northern Italian Industries.[2]

One explanation for the success of such agglomerated industries is that physical proximity facilitates the diffusion of knowledge and innovations among firms. The idea that knowledge might spill between firms in the same location was an important element of a broader theory that Marshall (1920) proposed to explain why firms tend to locate near one another. More recently, New Growth theorists revived general interest in knowledge spillovers and other externalities as possible explanations for the persistently divergent fortunes of different countries and regions. [3]

The long-term success of the Taiwanese electronics industry can be attributed to its ability to continuously produce new, high-margin, produces for the global market. Taiwanese electronics firms have often benefited from know-how provided by foreign customers and government research institutes. To remain on the leading edge of the product cycle, Taiwanese electronics firms have also relied on a network of subcontracting relationships. Groups of small and medium sized enterprises (SMEs) are frequently organized to assemble the expertise and production capacity to manufacture a new product. This organizational system, and a flexible labor market, has enabled Taiwanese firms to adapt quickly to changes in technology and demand. The Taiwanese firms are pressed to remain on the leading edge of the product cycle by the large South Korean conglomerates that are able to produce more mature products using significant economies of scale (See Wesphal 2002, Ernst 2000, and Hobday, 1995a). It seems likely that, as in Silicon Valley and Italy, the constant formation of business relationships would lead to knowledge spillovers as firms collaborate to incorporate new technologies into new products. The research question posed here is whether such knowledge spillovers are affected by geographic proximity.

Practical considerations make it particularly difficult to directly econometrically test for the existence of local knowledge spillovers. It is difficult to measure firm's knowledge and it is often thought that geographic proximity facilitates "informal"

---

1 Saxenian (1994) provides an in-depth analysis of the sources of the success of Silicon Valley and Paniccia and Carli mimeo reviews the Industrial District literature.

2 Saxenian (2001) describes the many parallels between Silicon Valley and the Taiwanese electronics industry, especially in the Hsinchu-Taipei corridor .

3 See Lucas (1993), Romer (1993), and Grossman and Helpman (1991) among others.

knowledge spillovers that are not captured in formal contracts or agreements between firms. These conditions essentially prohibit one from modeling the actual knowledge transmission process using existing data. Thus, this and other econometric work on the subject are limited to testing whether the existing data produce patterns that are consistent with local knowledge spillovers. Specifically, this paper proposes and implements an econometric method of estimating the role geographic proximity plays in determining firms' productivity growth.

Under the maintained hypothesis that a firm's knowledge is, at least partially, reflected in its total factor productivity (TFP), this paper uses micro panel data from the Taiwanese electronics industry in 1986, 1991, and 1996 to produce results that are consistent with the hypothesis that physical proximity facilitates the spread of knowledge among firms and that low productivity firms learn from their high productivity neighbors. To do so, various measures are constructed to characterize the distribution of the productivities of firms in each of ten 3-digit industries and 21 locations. Controlling for endogenous firm exit and the productivity effects of location-specific characteristics, a firm's future TFP is estimated as a function of its local industry-specific productivity distribution.

The next section presents a brief review of the literature on local knowledge spillovers. Section 3 develops a theoretical model of knowledge creation, spillovers, and firm behavior. Section 4 describes the data and provides some summary statistics. Section 5 presents an empirical model and Section 6 discusses the findings of various specifications of the empirical model. Section 7 revisits the critical maintained hypothesis that a firm's knowledge is reflected in its TFP and compares the "local knowledge spillover" interpretation of the results to other possible explanations. The final section provides some policy recommendations and concluding remarks. The construction of the index measure of TFP used in the estimation is described in the Appendix.

2 Literature Review

The empirical literature has explored knowledge spillovers between countries, between firms, from research centers to firms, and from a firm's headquarters to its various units. Most models either explicitly or implicitly contain two basic elements: knowledge and proximity. While the models differ in their empirical measures of these elements, most share a common structure. Each agent is assumed to have two sources of knowledge: internal and external (knowledge it is able to learn from other agents). The degree to which agents are able to access each other's knowledge is measured by their proximity to one another. Thus, in the case of inter-firm spillovers, a firm's external knowledge is generally constructed as the sum of the knowledge of other firms weighted by the firm's proximity to each. Many studies of knowledge spillovers have used measures of technological proximity, but the literature on *local* knowledge spillovers is limited to those that incorporate geography as a measure of proximity.

Early work on local knowledge spillovers consisted of case studies of the spread of specific new technologies. Griliches (1957) showed that the spread of the use of hybrid seeds by American farmers was facilitated by a strong "demonstration effect" whereby early adopters demonstrated the benefits of the hybrids to their local neighbors. Although this and other case studies have suggested that location plays an important role in the spread of knowledge, in each analysis the results have been limited to a single technology.

Other studies have sought to broaden the scope of the analysis of spillovers beyond a single technology. Rather than using one technology to represent knowledge, these studies have viewed knowledge more generally as the product of activities such as research and development (R&D). Using a unique data set on patent registrations and citations to measure knowledge production and the technological proximity of firms, Jaffe (1986) estimated the spillover effects of firms' R&D expenditures on their technological neighbors' patent activity. Jaffe, Trajtenberg and Henderson (1993) combined Jaffe's patent data with location data to estimate the probability that two firms share the same location as a function of whether they have cited each other's patents. The results suggest that location plays a significant role in the spread of ideas, as measured by the patent data. Jaffe, Trajtenberg (1997 and 1999) considered the international aspect of knowledge spillovers by comparing the rates of citations that US patents receive from domestic and foreign inventors. Hu and Jaffe (2000) did the same type of analysis focusing on Taiwanese and South Korean citations of US and Japanese patents. These studies found that US patents are significantly more likely to be cited by US inventors. This type of detailed data enables a rich characterization of the spillovers process; however, it is not available for most countries.

While Jaffe measured the effect of spillovers on the knowledge production process itself (new patents), most studies have estimated the effect of spillovers on a firm's production productivity instead. These types of studies have hypothesized that knowledge is discovered through R&D, imported through direct foreign investment (FDI), or learned through exporting experience. In addition, each of these sources of knowledge is thought to potentially spillover from one firm to another. Commonly the magnitude of these spillovers has been estimated by including measures of both internal and external knowledge in a standard production function or, alternatively, by assessing the effects of the knowledge stock on a constructed measure of productivity.

R&D expenditures have been used as a measure of knowledge by Coe and Helpman (1995), Basant and Fikkert (1996), Adams and Jaffe (1996) and Bernstein and Yan (1997). Among these authors, only Adams and Jaffe addressed the issue of local knowledge spillovers by including location as a measure of proximity in their study of intra-firm spillovers. Using plant-level data, they found that the physical distance between a plant and its firm headquarters partially determines the extent to which the plant benefits from its firm's R&D.

Studies that have addressed the potential spillovers from FDI have hypothesized that foreign firms import and demonstrate technologies that are useful to domestic firms. Firm and plant level data have been used to estimate the magnitude of FDI spillovers in studies by Haddad and Harrison (1993), Blomstrom and Sjoholm (1998), Aitken and Harrison (1999) and Konings (2001). Aitken and Harrison (1999) included location as an element of proximity to test for local spillovers from FDI. Using plant level data from Venezuela, they constructed FDI knowledge stocks for both industries and locations and estimated the spillover effects from these stocks in a standard production function. Their results suggest that while FDI has positive spillovers among firms in the same 3-digit industry group, it actually has negative spillovers among firms in the same location. Konings (2001) found similar evidence using data from Eastern European countries. Smarzynska (2001) hypothesized that foreign investors are more likely to transfer knowledge to their suppliers in upstream industries that to their competitors in the same industry. Using data from Lithuania, Smarzynska found evidence of such backward linkages, but no evidence that location was an important factor in such spillovers.

Along with R&D and FDI, exporting may be an important source of knowledge in developing countries if firms that export gain valuable product design information and processing technology from their foreign customers. Clerides, Lach and Tybout (1998) constructed a model that simultaneously estimates a firm's productivity and its decision to export. Using firm-level data from Colombia, Mexico and Morocco, the authors found that firms tend to get a one-time productivity boost when they begin exporting. Using data on firms' locations, the authors extended the analysis to address the issue of local spillovers from learning-by-exporting. They concluded that experienced exporters may demonstrate to their non-exporting neighbors *how* to export, but non-exporting firms do not benefit from the *knowledge* that their neighbors gain through exporting.

Many studies have found that R&D, FDI, or export experience have direct effects on a firm's own productivity, and several studies have also found evidence of knowledge spillovers using measures of technological proximity. Evidence of local knowledge spillovers has been found in the few studies that have used location data from developed countries. However, studies that have used data from developing countries have not found evidence of local knowledge spillovers from specific sources of knowledge such as FDI and exporting experience.

While much of the empirical literature uses firm-level data to assess the effects of local knowledge spillovers *between firms*, some papers use location data to assess the spread of knowledge *within locations*. To measure the ease with which knowledge flows within locations, this latter group of papers have used location characteristics such as the variety of industrial output and industrial concentration ratios as proxies for local information dispersion. For example, Gleaser, Kallal, Scheinkman and Shleifer (1992) used these two proxies to predict employment growth in US cities and industries over a 31-year period. The authors found evidence that local knowledge spillovers occur within industries but not between industries. Forni and Paba (2002) used a similar approach to investigate slipovers within Italian industrial districts.[4] A common criticism of models that use location characteristics as proxies to measure information dispersion is that the proxies may be correlated with other location characteristics, and thus the estimation results may be measuring the effects of something other than knowledge spillovers.

The empirical literature has found support for the hypothesis that physical proximity facilitates the spread of knowledge between firms in developed countries such as the US. It is surprising that these results have not been confirmed using data from developing countries because firms in developing countries can also use direct observation and interpersonal relationships as effective conduits for knowledge.

A possible explanation for the lack of evidence of local knowledge spillovers in developing countries is that studies, such as Aitken and Harrison (1999), Clerides, Lach and Tybout (1998) and Smarzynska (2001), have focused on the productivity effects of *specific* sources of knowledge. Instead of focusing on specific sources of knowledge, this paper uses TFP to reflect a firm's knowledge (regardless of its source). Measures of TFP capture the effects of differences in product design, processing technologies, organizational technologies, and/or managerial skill. Each of these differences can be interpreted as part

4 For other examples of location studies see Audretsch and Feldman (1996) and Ciccone and Hall (1996).

of a firm's collective knowledge, and each is also a potential source of knowledge spillovers. If firms can observe other firms in the same location, they may improve their own TFP by adopting and improving upon the technologies of their neighbors. However, measures of TFP also commonly capture other differences between firms, such as returns to scale or structural market power, that are not considered knowledge. By using TFP as a more general measure of a firm's knowledge, the model can be estimated using a wide variety of micro-level data sets. The model has broader applicability because many data sets from developing countries contain limited data on R&D, FDI and export behavior, but sufficient data to calculate TFP.

The next sections develop and econometrically estimate a model of local knowledge spillovers where a firm's knowledge determines its productivity. Strictly speaking, the econometric results presented in Section 6 offer evidence of local *productivity* spillovers. These finding are consistent with local knowledge spillovers, but like many other empirical studies, the data and the estimation technique do not account for the actual mechanisms through which knowledge passes from one firm to another. Section 7 discusses the potential pitfalls of using TFP to measure a firm's knowledge and of interpreting the results as proof of local knowledge spillovers.

3 Theoretical Model of Productivity Evolution and Firm Exit

An empirically testable theoretical model of dynamic local knowledge spillovers should contain several basic elements. First, it should specify a source of new knowledge. Second, it should also include a measure of geographic proximity in order to assess the importance of geography in the spillover process. Third, if the theoretical model is to be tested using firm-level panel data, it should also provide an explanation for why firms exit. Endogenous turnover may play an important role in empirically estimating spillover effects because it determines which firms are observed in the data in each period.

Firms in the model combine labor, capital and materials to produce output according to the production technology,

$$(1) \qquad Y_{it}\left(w_{it}, l_{it}, k_{it}, m_{it}\right)$$

where Y_{it} is a firm's total sales, and l_{it}, k_{it}, and m_{it} are the firm's number of workers, value of capital and value of materials respectively. The parameter, w_{it} represents a firm's productivity, a measure of its ability to combine its inputs efficiently. This ability arises from the institutional knowledge of the firm which is embodied in its workforce and management. The *i* and *t* subscripts indicate firms and discrete time periods respectively.

A firm's productivity evolves over time according to a markov process that is governed by the firm's current internal knowledge (its own productivity) and its external knowledge (the productivity of other firms). Formally, a firm's productivity in time *t+1* is drawn from a family of distributions,

$$(2) \qquad F\left(w_{it+1} \mid w_{it}, \Omega_{it}^{I,L}, x_{it}\right)$$

which depend on its internal knowledge (its current productivity, w_{it}) and its external knowledge stock, $\Omega_{it}^{I,L}$, which measures the productivity of other firms in the same location and/or industry. The distribution $F(w_{it+1} \mid \bullet)$ is defined such that a firm with higher current w_{it} or $\Omega_{it}^{I,L}$ draws its future knowledge from a distribution that first order stochastically dominates the distribution from which a firm with lower current w_{it} or $\Omega_{it}^{I,L}$ draws its future knowledge. This specification of the productivity evolution process is based on a general equilibrium model of entry and exit model proposed by Hopenhien (1992).[5]

The productivity evolution process captures the effect of knowledge spillovers because firms combine their internal and external knowledge to produce new knowledge. One may think of this as a knowledge production process whereby firms generate new ideas by combining their knowledge with the knowledge of their neighbors. This specification of the knowledge generating process is especially applicable to industries where imitation and innovation are intertwined and collaboration in an important means of generating incremental technological improvements. It is based on the principle of "recombinant growth" modeled by Weitzman (1998).[6] The effect of the knowledge generation process is lagged one period because the collaboration process takes time and new ideas or technology cannot be assessed and implemented immediately.

In addition, as technology advances and products and markets change, the knowledge needed to serve these markets also changes. Therefore, in a process of creative destruction, old knowledge may be rendered obsolete and replaced with new knowledge and the value of firm's internal knowledge stock may depreciate over time.

As in Hopenhayn's 1992 model, a firm decides whether to exit or remain in operation by solving it dynamic optimization problem to maximize the present discounted value of its future profits. In each period, the firm chooses to exit if its scrap value exceeds its present discounted value of future profits. Due to the Markov structure of the productivity evolution process, a firm's exit decision only depends on the current values of w_{it} and $\Omega_{it}^{I,L}$.[7] The firm exits if its productivity fails to meet a given threshold and the firm's binary decision rule can be represented by

$$(3) \qquad S_{it} = \begin{cases} 1 & if \quad w_{it} \geq \underline{w_{it}}\left(x_{it}, \Omega_{it}^{I,L}\right) \\ 0 & if \quad w_{it} < \underline{w_{it}}\left(x_{it}, \Omega_{it}^{I,L}\right) \end{cases}.$$

In (3) the firm's productivity threshold, $\underline{w_{it}}$, is a latent variable which depends on

---

5 The partial equilibrium model presented here analyzes a firm's exit decisions but does not characterize the evolution of the entire population of firms as done in Hopenhien (1992). It is similar to that used by Aw, Roberts and Winston (2002) and Aw, Chen, and Roberts (2001) which investigate the effects of export participation and R&D on a firm's productivity.

6 Weitzman cites the example of Edison's "electric candle" as a combination of the traditional technology and modern carbon filament.

7 The firm's dynamic decision can be summarized in the Bellman's equation,

$$V\left(w_{it}, x_{it}, \Omega_{it}^{I,L}\right) = Max\left\{\Theta, Sup\left[p\left(w_{it}, x_{it}\right)\right] + bV\left(w_{it+1}, x_{it+1}, \Omega_{it+1}^{I,L} \mid \Psi_t\right)\right\}.$$

the firm's individual characteristics such as size and age as well as its external knowledge stock. The observed binary choice variable, S_{it}, takes a value of 1 if a firm continues and 0 if a firm chooses to exit.

Firm turnover, particularly exit, plays an important role in the empirical investigation of spillovers because turnover determines which firms are observed at any given time. This model, which incorporates both spillovers and endogenous firm turnover, provides a theoretical structure for the empirical investigation of local productivity spillovers in Sections 5 and 6.

4 A Summary of Location Data

Every five years the Statistical Bureau of Taiwan's Executive Yuan conducts a census of the Taiwanese manufacturing sector. Among the data collected are information on each firm's total sales, total employment, value of capital stock, and expenditures on wages, materials and subcontracting. The details of the construction of the multilateral index TFP measure used in the empirical model and more details about the data are given in the Appendix. Because the observations in the cross-sections are linked across the years (1986, 1991, and 1996) these data can be used to track the evolution of a firm's productivity over time and to analyze entry and exit patterns.

The Bureau also records each firm's geographic location at the township and village level and assigns each firm to a 3-digit industry classification.[8] In its summary report of the census, the Bureau divides Taiwan into 23 major geographic areas: 16 counties, 5 cities, and 2 municipalities.[9]

There are two important general observations about the data that are relevant for the estimation of the empirical model. First, the Taipei area (municipality and county) was home to a large proportion of the total population of firms, accounting for 50% of the population in 1986 and 52% of the population in 1991. Second, there was a significant amount of entry and exit; between 1986 and 1991 1,721 firms exited and 3,692 entered, and in the period between 1991 and 1996 2,271 firms exited and 3,284 firms entered. The empirical model accounts for the econometric issues that arise from the entry and exit patterns and the model is estimated both with and without the firms in the Taipei area.

The empirical model addresses the question of intra-industry local productivity spillovers and therefore it exploits the variation in the number of firms and median TFP of firms within each 3-digit industry across the 21 locations. Figure 1 illustrates this important variation in the populations of Video and television manufacturing firms in three sample locations: Taichung County, Changwa County and Miaoli County. The three histograms in Figure 1 report the number of firms in each location in each TFP range. It is evident that firms in each of these three locations have different numbers of neighbors; a firm in Miaoli County has 39 neighbors in the same location whereas firms in Taichung, and Changwa Counties have 13 neighbors. The average productivity of a firm's neighbors also varies across the locations; firms in Taichung County have relatively low productivity neighbors, firms in Changwa County have high productivity neighbors and firms in Miaoli have many neighbors with moderate median productivity. The empirical model exploits the variation in firms' number of neighbors and the productivity of neighbors to estimate to

---

8 During the time period covered by the data the Census Bureau refined its 3-digit industry classifications. To maintain consistency throughout the panel, firms were assigned to 3-digit industries according to the less detailed 1986 system.

9 The analysis excludes two locations that had fewer than ten firms in each year.

effects of these differences on a firm's TFP.

5 An Empirical Model of Local Knowledge Spillovers

The structure of the empirical model parallels that of the theoretical model, which specifies equation (2) that governs the evolution of a firm's knowledge over time and equation (3) that governs a firm's exit behavior. The empirical model of local knowledge spillovers specifies reduced forms of these two equations and estimates them jointly as a Heckman selection model. TFP is used as a measure of knowledge in both equations.

In the theoretical model, a firm draws its future knowledge from a distribution that depends on its current internal and external knowledge as well as other firm characteristics. The empirical model specifies the evolution of a firm's TFP from year t to year $t+1$ as a reduced form knowledge evolution equation:

$$w_{it+1} = a_0 + a_1 w_{it} + a_2 extknow_{it} + a_3 w_{it} * extknow_{it} e_{it+1}.$$

The variable $extknow_{it}$ characterizes the local external knowledge stock available to each firm and the interaction between w_{it} and $extknow_{it}$ captures the possibility that some firms benefit more from their local external knowledge stock than others. The effects of these measures are the focus of the analysis of local knowledge spillovers. e_{it+1} is a random error term with a standard normal distribution. Each estimated coefficient in the knowledge evolution equation can be interpreted as the effect of the associated independent variable on the mean of the distribution from which a firm's future knowledge is drawn.

The theoretical model also specifies an exit decision based on a firm's present discounted value of future profits (which depends on its future knowledge). This binary exit decision is empirically modeled as a reduced form selection equation,

$$S_{it+1} = b_0 + b_1 I(E_{it}) + b_2 \ln(age_{it}) + b_3 \ln(k_{it}) + b_4 \left(\ln(k_{it})\right)^2 + b_5 w_{it} + b_6 extknow_{it} + u_{it+1},$$

where $S_{it} = 1$ if the firm chooses to continue and $S_{it} = 0$ if the firm exits. The dummy variable, $I(E_{it})$, is turned on for firms that have entered between the last census year and the current census year and $\ln(age_{it})$ measures the natural log of a firm's age. They are included in the estimation because recent entrants and young firms are generally more likely to exit. The measures of capital stock, $\ln(k_{it})$ and $\left(\ln(k_{it})\right)^2$, are included in the selection equation to control for the effects of a firm's size on its exit decision. Theory suggests that larger firms would be more willing to cover the variable costs of operation and continue to produce even if they draw an unfavorable TFP. u_{it+1} is random error term with a standard normal distribution.

The endogenous optimal exit behavior specified in the theoretical model becomes an important aspect of the empirical model because turnover determines which firms are active and observable in each period. Correlation between the random unobserved shocks that affect a firm's future TFP and the random shocks that affect its exit decision would bias parameters of an independently estimated knowledge evolution equation. A standard Heckman selection model was employed to estimate the two equations simultaneously and thus eliminate the selection bias. By accounting for possible correlation between the random error terms e_{it+1} and u_{it+1}, the parameters of the evolution equation were estimated conditional upon a firm's survival.

The knowledge production process specified in the theoretical model prescribes a specific role for knowledge spillovers in the knowledge evolution process, but it does not specify how a firm's external knowledge should be measured empirically. The ability to construct a measure of proximity between any given pair of firms is an important advantage of using detailed data such as the patent data used by Jaffe (1986) and Jaffe, Trajtenberg and Henderson (1993), because the links between pairs of firms make it possible to assess the spillovers that result from these pair-wise interactions. Without such detailed data, the pair-wise interactions must be proxied as interactions between each firm and the groups of firms to which it belongs. Thus, the distribution of knowledge within each group represents the external stock of knowledge available to the members of each group. The empirical model groups firms according to their locations; within each location firms are also grouped according to their 3-digit industry. Each firm's external knowledge is represented as the distribution of the knowledge of other firms in its location and the distribution of the knowledge of other firms in its location *and* its industry.

Since a firm's external knowledge depends on the number of interactions the firm has with other firms as well as the level of knowledge accessed in each interaction, it can be empirically proxied by two measures: the *median TFP* of all firms in a particular location and the *number of firms* in the location. The first measure captures the notion that higher TFP firms provide better external knowledge from which their neighbors can produce new ideas. The second measure captures the notion that firms with more neighbors have either more opportunities to produce new ideas or a greater variety of external knowledge. To estimate the effects of intra-industry local knowledge spillovers, these measures are constructed for each location and for each 3-digit industry within each location.

6 Results of Local Knowledge Spillovers

Five specifications of the model are estimated to assess the empirical importance of intra-industry local knowledge spillovers within the 3-digit industries that comprise the 2-digit electronics industry. The first specification does not include measures of external knowledge but establishes a baseline for the remaining specifications. The second specification includes measures of each location's TFP distribution. The third specification tests for intra-industry local knowledge spillovers by adding measures of external knowledge in each 3-digit industry within each location. The fourth specification uses a different characterization of the 3-digit industry-specific local knowledge stocks to support the findings of the third specification. The final specification includes interaction terms between local knowledge stocks and TFP to test whether low or high productivity firms are more likely to benefit from any spillovers. The data are pooled across the two years for which both future and current TFP measures are available (1986 and 1991). While the pooled results are always consistent with the un-pooled results, some results are not statistically significant in each year when the model is estimated on each year separately. Table 2 reports the results of the knowledge evolution equation and Table 3 reports the results of the selection when the two equations are estimated jointly.

Column 1 of Table 2 reports the estimated parameters of the baseline TFP evolution equation. It includes a year dummy, $year1986d_{it}$, and the natural log of firms' TFP, w_{it}. Column 1 of Table 3 reports the estimated parameters of the selection equation. In addition to the parameters of the evolution equation, the selection equation includes: an entrant dummy, $I(E_{it})$, the natural log of firms' age in years, $\ln(age_{it})$, the natural log of capital, $\ln(k_{it})$, and its square, $\ln(k_{it})^2$.[10] The additional information provided by the capital measures in the selection equation help to identify the joint specification.

The predictions of the theoretical model are confirmed by the estimated parameters of the empirical knowledge evolution equation reported in Column 1 of Table 2. The coefficient on w_{it} suggests that, on average, firms with higher current TFP will draw higher future TFP, and thus a firm's knowledge does not depreciate completely during the five-year intervals between census years. For example, two firms with current TFPs that differ by 10% will draw their respective future TFPs from two distributions with means that differ by 1.9%. The more rapid general productivity growth that occurred between the 1991 and 1996 census years is reflected in the negative coefficient on the 1986 year dummy.

The theoretical model makes several predictions regarding firms' endogenous exit decisions. Consistent with these predictions, the first column of results in Table 3 suggest that larger and more productive firms are more likely to choose to continue while recent entrants are more likely to exit. The negative coefficient on the square of the capital stock indicates that the effect of size tends to diminish. The estimated correlation between e_{it+1} and u_{it+1} indicates that random shocks that increase a firm's future TFP are negatively correlated with random shocks that increase the likelihood that a firm will chose to continue.[11]

The second specification of the model introduces measures of the TFP distribution of each location: $medw_{it}^{L}$ measures the natural log of the median TFP of all electronics firms in the location and $\# frms_{it}^{L}$ measures the natural log of the total number of electronics firms in the location. The results of the joint estimation of the knowledge evolution equation and the selection equation are reported in the second column of Table 2 and Table 3 respectively. The positive and significant coefficient on $medw_{it}^{L}$ in the evolution equation would seem to suggest that a high median local TFP offers a firm the opportunity to access superior external knowledge and to produce more (or more fruitful) new ideas.

One possible explanation for the large positive coefficient on $medw_{it}^{L}$ is the omission of important location characteristics from the model. Variables such as port facilities or cheap effective labor, which are available to all electronics firms in a given location but are missing from the model, may function as local public goods and thus affect the general level of TFP in each location. Therefore, the coefficient on $medw_{it}^{L}$ may be picking up the effects of these missing variables and should not be interpreted as

10 The entrant dummy indicates firms that have entered between year t-1 and year t. An earlier version of this paper included the entrant dummy and age variable in the productivity evolution equation to capture the possibility that recent entrants and other younger firms may have different productivity evolution patterns.

11 A test for serial correlation finds that one cannot reject the null hypothesis of no serial correlation in e_{it+1}.

knowledge spillovers. If $medw_{it}^{L}$ captures the effects of local public goods available to firms in all 3-digit industries within a location, then this measure can be used to control for these missing location characteristics when estimating the degree of local knowledge spillovers between firms in the same 3-digit industry and location (as done in the next specification).

The variable $\#\,frms_{it}^{L}$, which represents the number or variety of opportunities a firm has to combine knowledge and produce new ideas, also significantly affects a firm's future TFP. This result is consistent with the theory that more neighbors offer more opportunities for spillovers. However, it is also consistent with the theory that more firms chose to locate near other existing public goods, such as pools of skilled labor.

The inclusion of $medw_{it}^{L}$ and $\#\,frms_{it}^{L}$ has predictable effects on the remaining parameters of the model. Differences in the measures of each location's knowledge stock across years capture the time period effect attributed to the year dummy in the first specification. The reduction in the coefficient on w_{it} may be attributed to the positive correlation between current TFP and the measures of knowledge stocks, supporting the claim that the model is missing important local characteristics.

The second specification demonstrates that location is an important element of the evolution of a firm's TFP, but it is unable to distinguish the effects of local knowledge spillovers from the effects of other location specific characteristics. The third specification incorporates information about each firm's 3-digit industry classification to assess whether the location effects are stronger when firms share the same industry. Studies such as Aitken and Harrison (1999) and Gleaser et al. (1992) have provided empirical evidence to support the intuitive hypothesis that industry affiliation is an important element of technological proximity. In the context of the current model, this hypothesis suggests that firms generate more new knowledge by combining their knowledge with firms in the same 3-digit industry than by combining knowledge with firms in other 3-digit industries.

Two measures of local 3-digit industry specific knowledge stocks are constructed to test the hypothesis that local knowledge spillovers are stronger among firms that share the same industry. For each location/industry combination $medw_{it}^{I,L}$ measures the natural log of industry-specific local median TFP, and $\#\,frms_{it}^{I,L}$ measures the natural log of the number of firms. These measures are added to the model in the third specification. The general location measures used in the second estimation play an important role in this specification by controlling for the productivity effects of other local public goods used by firms in all industries. As long as the other local public goods are not specific to each 3-digit industry, correlation between firms' TFP and $medw_{it}^{I,L}$ or between firms' TFP and $\#\,frms_{it}^{I,L}$ will not bias the results. Consequently, the parameters on $medw_{it}^{I,L}$ or $\#\,frms_{it}^{I,L}$ will identify intra-industry local knowledge spillovers while controlling for general location differences.

The results of the third specification (reported in the third columns of Table 2 and Table 3) indicate that $medw_{it}^{I,L}$, the measure of median industry TFP within each location, has a significant, but negative, effect on the evolution of a firm's TFP. Thus, the productivity enhancing local characteristics captured by $medw_{it}^{L}$ do not seem to be industry specific. The coefficient on the number of firms in each industry within each location, $\# frms_{it}^{I,L}$, indicates that having more opportunities to learn from neighbors in the same industry has a positive and statistically significant effect on future TFP. There is good reason to believe that this evidence of local scale economies at the industry level captures local knowledge spillovers rather than the effect of industry-specific local public goods because, without the promise of higher TFP, there is no compelling reason for firms in a particular industry to favor a particular location. Thus, $\# frms_{it}^{I,L}$ would not necessarily be correlated with location characteristics that are not captured by the general location measures.

The magnitude of the local knowledge spillovers also makes economic sense. Compared to the average firm, a firm that has twice as many neighbors from the same industry will draw its future TFP from a distribution with a median that is 2.1% higher than the average firm's. A 2% return on the number of location/industry neighbors is economically significant because there are many cases where one location/industry has several times the population of another location/industry. For example, in 1991 there were 49 Data Storage firms and 31 Video & Radio firms in Taoyaun County, while in the same year there were only 11 Data Storage firms but 62 Video & Radio firms in neighboring Shinchu County.

The fourth specification of the model lends support to the claim that $\# frms_{it}^{I,L}$ captures the effects of local knowledge spillovers. If high productivity neighbors are better sources of knowledge than low productivity neighbors, then the spillovers associated with the number of high productivity neighbors should be greater than the spillovers associated with the number of low productivity neighbors. To test this hypothesis, TFP quartiles were constructed for each 3-digit industry. Then, for each location/industry a count was made of the number of firms drawn from each of the four industry-specific quartiles. For example, $Q1\# frms_{it}^{I,L}$ for firm *i* in period *t* is the natural log of the number of firms in the same location and industry that fall in the top quartile of the TFP distribution of firm *i*'s 3-digit industry in period *t*. The variables $Q1\# frms_{it}^{I,L}$ through $Q4\# frms_{it}^{I,L}$ record the natural log of the number of firms in each location drawn from each of the industry-specific quartiles and replace $medw_{it}^{I,L}$ and $\# frms_{it}^{I,L}$ as the characterization of the location/industry TFP distributions. The median TFP of the location, $medw_{it}^{L}$, and the number of firms, $\# frms_{it}^{L}$, are retained in the final specification to account for the effects of other local public goods.[12]

As reported in Column 4 of Table 2, the coefficient on the number of neighbors from the top industry TFP quartile, $Q1\# frms_{it}^{I,L}$, is positive and significant while the coefficients on the number of firms from the remaining quartiles are insignificant (on the second and third quartile they are actually negative). These results indicate that high productivity firms are the only significant sources of knowledge spillovers, which suggests that firms benefit most from combining their internal knowledge with the external knowledge of those neighbors that have the highest TFP. Compared to the average firm, a

---

12 $\# frms_{it}^{I,L}$ is not included the fourth and fifth specifications because it would be nearly perfectly collinear with the quartile counts.

firm with twice as many high productivity neighbors from the same industry can expect to have a future TFP that is 3.4% higher than the average firm's. The negative and significant parameter on $\# frms_{it}^{L}$ in this specification may indicate a general congestion effect of having more firms competing for limited local resources such as land.

The results, thus far, indicate that high productivity neighbors are beneficial to other firms. However, this says nothing about which firms are better able to take advantage of apparent benefits provided by high productivity neighbors. The benefits may primarily accrue to other high productivity firms if low productivity firms lack the absorptive capacity to take advantage of their interactions with their high productivity neighbors. Alternatively, evidence that lower productivity firms benefit more from having high productivity neighbors would be consistent with knowledge spillovers. To address this empirical question, the final specification includes interactions between a firm's TFP and the quartile counts. The results reported in column 5 of Table 2 indicate that firms with lower productivity benefit more from having high productivity neighbors than firms with higher productivity. The coefficient on $Q1\# frms_{it}^{I,L}$ changes from 0.034 in the fourth specification to 0.046 in the final specification. However, the negative and statistically significant coefficient on the interaction term between $Q1\# frms_{it}^{I,L}$ and w_{it} indicates that the higher productivity firms benefit less from having high productivity neighbors than lower productivity firms. Specifically, only firms with TFP below 0.57 benefit from having additional high productivity neighbors. This evidence is consistent with the view that lower productivity firms learn more from their interactions with higher productivity neighbors, a true knowledge spillover effect.

Given this evidence of local knowledge spillovers one can propose policy recommendations. Generally one would like to encourage firms to improve their productivity and to locate in areas that would maximize their spillover potential. Although this paper does not model firms' investment decisions, there are several actions that firms may take to increase their own productivity. Aw, Roberts and Winston (2002) show that export market participation can have important effects on productivity, especially when it is combined with R&D investments. Since individual firms do not account for the external, spillover, effects of their investments in these activities, they will invest at less than socially optimal levels. Therefore, society would benefit from providing incentives for investments. In addition, because the spillovers identified in the econometric results depend on physical proximity, a social planner would want to encourage such productivity enhancing investments by high productivity firms in locations where they would have the most spillover impact, areas that have large numbers of low productivity firms that could benefit from such spillovers.

7 A Critical Look at the Spillover Results

One should carefully consider to what extent such findings, which are consistent with local knowledge spillovers, might actually offer evidence or proof of local knowledge spillovers. There are two primary issues to consider: Does TFP capture elements of a firm's productivity, such as knowledge, that could spillover? What other potential explanations are also consistent with the results?

There are several reasons to believe that differences in TFP capture more than differences in knowledge. For instance: true labor inputs might be miss-measured if differences in workers' skills are not considered, other inputs might be miss-measured if they are measured by expenditures rather than by units, firms with market power might appear to be more productive if revenues are used as a measure of output instead units and, larger firms might appear to be more productive if they benefit from economies of scale (which are assumed to be constant when constructing the TFP measure). Even so, several studies have confirmed a statistical relationship between expenditures on activities, such as R&D, that are thought to produce knowledge and measures of firm-level TFP.[13]

These valid criticisms of using TFP as a measure of technology or "knowledge" might affect how one should interpret the econometric results, which highlight the importance of geography. To assess the validity of the "knowledge spillovers" interpretation, consider what else might spill over between firms in the same industry and location.

To the extent that differences in TFP are the result of errors in input measures, one might expect that firms that share access to a common input resource, such as skilled labor or low-cots energy, would have higher average measured TFP than firms in other locations. It is also clear that such benefits might persist over time, so that firms with access to the common resource could expect higher future TFP independent of their current TFP. However, as described, the estimated insignificant parameters on $medw_{it}^{L}$ and the negative and significant parameter of $medw_{it}^{I,L}$ indicate that the results are probably not biased by general or industry-specific local input resources.

Market power in such a dynamic global industry is likely to reflect a firm's ability to produce a product with unique characteristics or qualities at a given time rather than any structural market conditions. Instead, such transitory market power might capture a leading firm's knowledge, which can be observed and copied by other firms rather than a lasting ability to charge a higher price for a given product. Moreover, it is difficult to reconcile the results with the possibility that the TFP measure captures lasting structural market power. In other contexts, it is clear that small firms may benefit from the presence of a large firm that dominants the local market. However, it is difficult to understand why having additional dominant firms is even better, as the results would indicate.

The measurement issues that arise from assuming constant returns to scale in the production function could be consistent with the econometric results if scale spills over from one firm to another. That is, small firms that are located near large (higher TFP) firms might grow faster, and thus achieve greater economies of scale. However, this hypothesis can be tested more directly by dividing firms into size quartiles rather than TFP quartiles. Doing so fails to confirm the hypothesis that size (not TFP) produces spillovers.

Even if one takes TFP as a measure of our ignorance about the production process, the results indicate that there is something important about geographic proximity and productivity. The results are consistent with the interpretation that the TFP measure captures a firm's knowledge, among "other things". And, further consideration of the results indicates that the "other things" probably do not drive the econometric results.

8 Conclusion

Theoretical models have suggested both that knowledge spillovers are potentially of great economic importance and that such spillovers may be facilitated by physical

---

13 See Griliches (1998) and Aw, Roberts, Winston (2002).

proximity. Using data on R&D and patent citations, some studies have found empirical evidence that physical proximity plays an important role in the spread of knowledge in developed countries. Although there are reasons to expect physical proximity to facilitate the spread of knowledge in developing countries as well, local knowledge spillovers have not been identified using data from the developing world. The lack of evidence of local knowledge spillovers in developing countries may be due to the fact that the existing literature has focused on the spillovers associated with specific knowledge sources such as FDI and export participation. This paper takes a broader view of the sources of spillovers by recognizing that knowledge is a potentially important element of a firm's productivity.

The theoretical model described in this paper draws on Hopenhayn's (1992) model of industry evolution to describe the evolution of firms' productivities and endogenous exit decisions. In Hopenhayn's model, a firm's productivity in each period is a random draw from a family of distributions determined by the firm's previous productivity; this paper suggests that the randomness assumed in Hopenhayn's model may be the result of the uncertainty of the knowledge production and absorption process.

The empirical model tests for intra-industry local knowledge spillovers in the Taiwanese electronics industry by estimating the dynamic productivity effects of knowledge stocks associated with each 3-digit industry within each county or metropolitan area. The evolution of a firm's knowledge is specified as a reduced form equation that estimates a firm's future TFP as a function of its current TFP, local industry-specific knowledge stocks, and other characteristics. The estimation controls for the productivity effects of local public goods by including measures of each location's TFP distribution and accounts for endogenous firm exit by employing a Heckman selection model.

The results suggest that intra-industry local knowledge spillovers are both economically and statistically significant; specifically, a firm's expected future TFP is positively affected by having more neighbors in the same industry. The existence of intra-industry knowledge spillovers is further supported by a separate specification that suggests that firms in the top 3-digit industry-specific TFP quartile (firms with large stocks of internal knowledge) are significant sources of knowledge spillovers while firms in the remaining quartiles are not. The final specification confirms that firms in the top TFP quartile offer greater benefits to their lower productivity neighbors than to their higher productivity neighbors. Thus, local knowledge spillovers are potentially an important source of productivity growth for the Taiwanese electronics industry. Importantly, it appears that the results are not consistent with other possible differences between firms that are captured by the TFP measure.

If the results indeed capture local knowledge spillovers, governments would want to consider various policies to encourage private investments in knowledge, especially among the most productive firms. Without such encouragement, private firms will make less than socially optimal investments in activities that generate knowledge because they will not account for the non-private social value of such investments. This paper is unable to identify what types of investments should be encouraged, but the results in Aw, Roberts, and Winston (2002) suggest that investments in R&D and export participation by Taiwanese electronics firm have significant effects on their productivities. To maximize the effect of such policies, the investment incentives should target locations where they could produce the greatest social benefit, areas where there are more less-productive firms that could benefit from the spillover effect.

Regardless of whether or not they indicate the presence of local knowledge spillovers, the results have possible policy implications. If the TFP measure captures something that is good for society, the results indicate the there is a positive spillover effect.[14] Thus, the results support policies that encourage general TFP-enhancing investments by high-productivity firms in targeted areas. However, the unique nature of the Taiwanese electronics industry limits the applicability of these results. They do not indicate that similar policies would necessarily be beneficial in other sectors or other countries.

The method of analyzing local knowledge spillovers developed in this paper can be extended in many interesting directions. While this paper assumes that all firms in a location access the same external knowledge stock, it is possible that the physical distance *between* firms *within* each location also determines the extent of knowledge spillovers. Approximate measurements of the physical distance between any two firms could be made using the more detailed location information included in the Taiwanese data, and the approximate distance between two firms could then be used to weight each firm's knowledge contribution to the other. Thus, the effect of local knowledge spillovers could be estimated using firm-specific, weighted average external knowledge stocks.

The Taiwanese manufacturing census also includes data on several other 2-digit industries that could be analyzed using the model presented in this paper. Comparisons across industries could be used to address the theoretical prediction that local knowledge spillovers are more important in industries with rapidly changing technologies such as electronics and less important in traditional industries such as textiles.

Because knowledge is measured as a TFP index, the methodology developed here does not require data on R&D expenditures or other specific measures of knowledge. As a result, the model can be applied to a wide range of firm-level data sets from countries where the spread of knowledge may have important economic effects, even though few firms make formal investments in R&D. Studies that examine spillovers in different countries could compare the importance of local knowledge spillovers in vertically integrated sectors, such as South Korean manufacturing, relative to the importance of spillovers in highly decentralized sectors, such as Taiwanese manufacturing.

14 This may not be the case if investments are made to secure lasting structural market power.

Figure 1: Productivity Distribution of Firms in the Video and Radio Equipment Industry in Three Counties in 1986

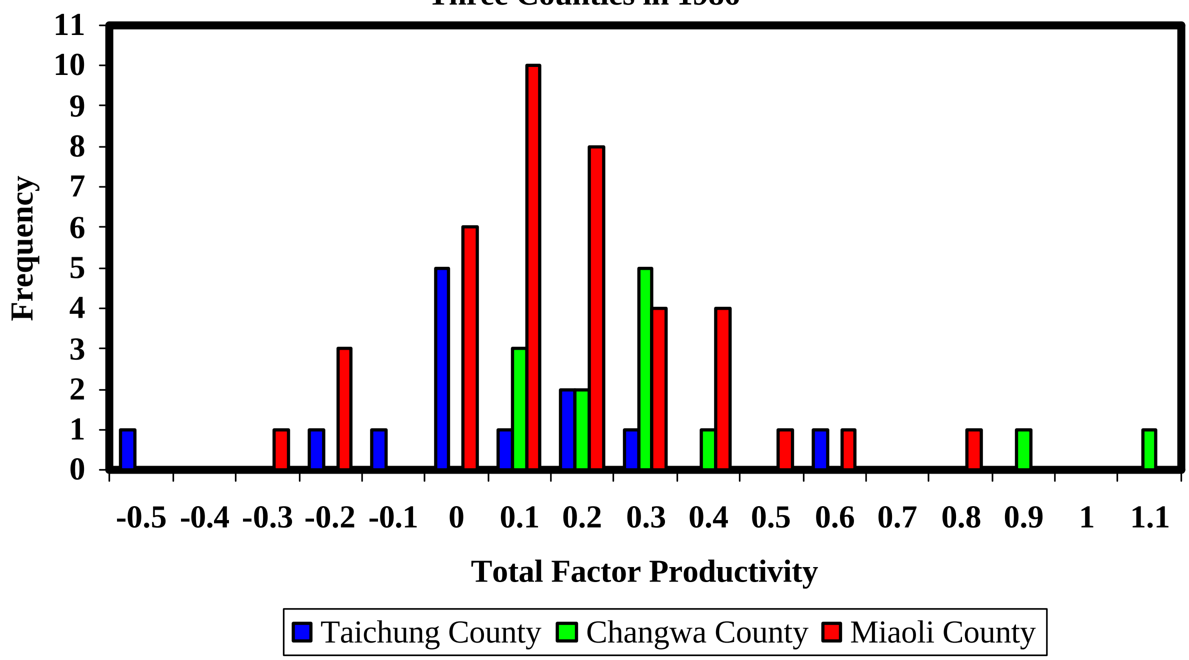

Table 1: Video and Radio Equipment Firms in Three Counties in 1986

Median TFP and Frequency

Location	Median w_{it}	# of firms
Taichung County	-0.012	13
Changwa County	0.220	13
Miaoli County	0.096	39

Table 2: Productivity Evolution Estimates

Maximum Likelihood Estimation of Selection Model - Dependent Variable: w_{it+1}

	Baseline	Location Measures	Location/Industry Measures	Industry Quartiles	Industry Quartiles with w_{it} interactions
constant	0.359* (0.010)	0.267* (0.028)	0.302* (0.029)	0.364* (0.035)	0.367* (0.036)
$year86d_{it}$	-0.046* (0.008)	-0.028* (0.009)	-0.030* (0.009)	-0.034* (0.010)	-0.034* (0.010)
w_{it}	0.193* (0.015)	0.184* (0.015)	0.179* (0.015)	0.174* (0.016)	0.181* (0.046)
$medw_{it}^{L}$		0.212* (0.071)	0.141 (0.100)	0.142 (0.078)	0.148 (0.078)
$\# frms_{it}^{L}$		0.006* (0.003)	0.066 (0.073)	-0.020* (0.006)	-0.020* (0.006)
$medw_{it}^{I,L}$			-0.014* (0.006)		
$\# frms_{it}^{I,L}$			0.021* (0.005)		
$Q1\# frms_{it}^{I,L}$				0.034* (0.010)	0.046* (0.011)
$Q2\# frms_{it}^{I,L}$				0.002 (0.013)	0.003 (0.015)
$Q3\# frms_{it}^{I,L}$				-0.013 (0.013)	-0.025 (0.016)
$Q4\# frms_{it}^{I,L}$				0.006 (0.011)	0.004 (0.013)
$Q1\# frms_{it}^{I,L} * w_{it}$					-0.081* (0.038)
$Q2\# frms_{it}^{I,L} * w_{it}$					-0.011 (0.052)
$Q3\# frms_{it}^{I,L} * w_{it}$					0.076 (0.052)
$Q4\# frms_{it}^{I,L} * w_{it}$					0.014 (0.041)
$Cov(e_{it+1}, u_{it+1})$	-0.64* (0.031)	-0.616* (0.037)	-0.621* (0.035)	-0.637* (0.034)	-0.637* (0.035)
log likelihood	-6736.1	-6718.0	-6707.2	-6361.8	-6358.2
sample size	9793	9793	9793	9330	9330

* indicates statistical significance at the 0.05 level

Table 3: Survival Equation Estimates

Maximum Likelihood Estimation of Sample Selection Model - Dependent Variable: S_{t+1}

	Baseline	Location	Location/Industry	Industry Quartiles	Industry Quartiles with w_{it} interactions
constant	-4.404* (0.368)	-4.623* (0.378)	-4.633* (0.377)	-4.692* (0.389)	-4.703* (0.391)
$year86d_{it}$	-0.157* (0.032)	-0.092* (0.047)	-0.093* (0.047)	-0.041 (0.051)	-0.040 (0.051)
$I(E_{it})$	-0.389* (0.037)	-0.341* (0.043)	-0.343* (0.043)	-0.299* (0.045)	-0.298* (0.045)
$\ln(age_{it})$	-0.008 (0.019)	-0.006 (0.019)	-0.007 (0.019)	-0.001 (0.019)	-0.001 (0.019)
$\ln(k_{it})$	0.863* (0.071)	0.845* (0.072)	0.841* (0.072)	0.814* (0.074)	0.812* (0.074)
$(\ln(k_{it}))^2$	-0.034* (0.003)	-0.033* (0.003)	-0.033* (0.003)	-0.032* (0.004)	-0.031* (0.004)
w_{it}	0.315* (0.051)	0.308* (0.051)	0.323* (0.052)	0.331* (0.053)	0.381* (0.161)
$medw_{it}^{L}$		0.352 (0.295)	0.725 (0.382)	0.819* (0.338)	0.811* (0.338)
$\# frms_{it}^{L}$		0.028* (0.012)	-0.392 (0.260)	0.059* (0.021)	0.060* (0.021)
$medw_{it}^{I,L}$			0.049* (0.020)		
$\# frms_{it}^{I,L}$			-0.022 (0.018)		
$Q1\# frms_{it}^{I,L}$				-0.109* (0.035)	-0.119* (0.039)
$Q2\# frms_{it}^{I,L}$				-0.006 (0.047)	-0.017 (0.051)
$Q3\# frms_{it}^{I,L}$				0.055 (0.047)	0.064 (0.053)
$Q4\# frms_{it}^{I,L}$				0.028 (0.038)	0.042 (0.044)
$Q1\# frms_{it}^{I,L} * w_{it}$					0.047 (0.134)
$Q2\# frms_{it}^{I,L} * w_{it}$					0.101 (0.183)
$Q3\# frms_{it}^{I,L} * w_{it}$					-0.067 (0.184)

$Q4\# \; frms_{it}^{I,L} * w_{it}$					-0.095 (0.145)

* indicates statistical significance at the 0.05 level

References

Adams, J. D. and A. Jaffe, "Bounding the effects of R&D: an investigation using matched establishment-firm data," *RAND Journal of Economics* 27(4) (1996), 700-721.

Audretsch, D. B. and M. P. Feldman, "R&D Spillovers and the Geography of Innovation and Production," *The American Economic Review* 86(3) (1996), 630-640.

Aitken, B., G. H. Hanson, A. E. Harrison, "Spillovers, Foreign Investment, and Export Behavior," *Journal of International Economics* 43(1-2) (1997), 103-132.

Aw, B. Y., X. Chen, and M. J. Roberts, "Firm-Level Evidence on Productivity Differentials, Turnover and Exports in Taiwanese Manufacturing," *Journal of Development Economics* 66 (2001) 51-86.

Aw, B. Y., S. Chung and M. J. Roberts, "Productivity and Turnover in the Export Market: Micro-Level evidence from Taiwan (China) and the Republic of Korea," *World Bank Economic Review* 14(1) (2000), 65-90.

Aw, B. Y., M. J. Roberts, and T. Winston, "Export Market Participation, Investments in R&D and Worker Training, and the Evolution of Firm Productivity," mimeo The Pennsylvania State University, 2002.

Basant, R and B. Fikkert, "The Effects of R&D, Foreign Technology Purchase, and Domestic and International Spillovers on Productivity in Indian Firms," *The Review of Economics and Statistics* (1996) 187-199.

Bernstein, J. I. and X. Yan, " International R&D Spillovers Between Canadian and Japanese Industries," *Canadian Journal of Economics* 30 (2) (1997), 276-291.

Blomstrom, M. and F. Sjoholm, "Technology Transfer and Spillovers: Does Local Participation with Multinationals Matter?," Working Paper No. 6816, NBER, Cambridge, MA, 1998.

Caves, D. W., L. R. Christensen and M. W. Trethaway, " U.S. Trunk Air Carriers, 1972-1977: A Multilateral Comparison of Total Factor Productivity," in T. G. Cowing and R.E. Stevenson (eds.), *Productivity Measurement in Regulated Industries*, (New York: Academic Press, 1981).

Caves, D. W., L. R. Christensen and W. E. Diewert, "Multilateral Comparisons of Output, Input, and Productivity Using Superlative Index Numbers," *Economic Journal* 92(365) (1982a), 73-86.

Caves, D. W., L. Christensen, and E. Diewert, "Output, Input, and Productivity Using Superlative Index Numbers," *Economic Journal* 92 (1982b), 73-96.

Ciccone, A. and R. E. Hall, "Productivity and the Density of Economic Activity," *The American Economic Review* 86(1) (1996), 54-70.

Clerides, S. K., S. Lach and J. R. Tybout, "Is Learning by Exporting Important? Micro-dynamic Evidence from Colombia, Mexico, and Morocco," *Quarterly Journal of Economics* 113(3) (1998), 903-47.

Coe, D. and E. Helpman, "International R&D spillovers," *European Economic Review* 39 (1995), 859-887.

Ernst, E., "Inter-organizational knowledge outsourcing: What permits small Taiwanese firms to compete in the computer industry?," *Asia Pacific Journal of Management* 17(2) (2000), 223-256.

Forni, M and S. Paba, "Spillovers and the Growht of Local Industries," *Journal of Industrial Economics* L(2) (2002), 151-171.

Glaeser, E. L., H. D. Kallal, J. A. Scheinkman, and A. Shleifer, "Growth in Cities," *Journal of*

Political Economy 100(6) (1992), 1126-1152.
Good, D. H., M. I. Nadiri, and R. Sickles, "Index Number and Factor Demand Approaches to the Estimation of Productivity," in H. Pesaran and P. Schmidt, *Handbook of Applied Econometrics*, Volume II: Microeconometrics, (Basil: Blackwell, 1997)
Griliches, Z., "Productivity, R&D, and Basic Research at the Firm Level in the 1970s," *American Economic Review* 76(1) (1986), 141-54.
Griliches, Z., *R&D and Productivity: The Econometric Evidence,* (University of Chicago Press, 1998).
Grossman, G. M. and E. Helpman, *Innovation and Growth in the Global Global Economy* (Cambridge, MA: Mit Press, 1991).
Haddad, M. and A. Harrison, "Are there positive spillovers from direct foreign investment?," *Journal of Development Economics* 42 (1993 , 51-74.
Heckman, J. J., "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating A Discrete Time-Discrete Data Stochastic Process," in C. Manski, and D. McFadden (eds.), *The Structural Analysis of Discrete Data* (Cambridge, MA: MIT Press, 1981)
Hobday, M., "Export-led technology Development in the four dragons: the case of electronics." *Economic Development and Cultural Change* 25 (1994), 333-361.
Hobday, M., *Innovation in East Asia: The Challenge to Japan* (Brookfield, VT: Edward Elgar, 1995a).
Hobday, M., "East Asian Latecomer Firms: Learning the Technology of Electronics," *World Development* 23(7) (1995b), 1171-1193.
Hopenhayn, H., "Entry, Exit, and Firm Dynamics in Long-Run Equilibrium," *Econometrica* 60 (1992), 1127-50.
Hu, Albert G. Z. and A. B. Jaffe. "Patent Citations and International Knowledge Flow: The Cases of Korea and Taiwan," *National Bureau of Economic Research* working paper No. 8528 (2001).
Jaffe, A. B., "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value," *American Economic Review* 76(5) (1986), 984-1001.
Jaffe, A. B. and M. Trajtenberg, "International Knowledge Flows: Evidence for mPatent Citations." *Economics of Innovation and New Technology* 8(1-2) (1999) 105-136.
Jaffe, A. B., M. Trajtenberg, and R. Henderson, "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." *Quarterly Journal of Economics* 108 (3) (1993), 577-598.
Konings, J., "The Effects of Foreign Direct Investment on Domestic Firms: Evidence from firm-level panel data in emerging economies," *Economics of Transition* 9(3) (2001) 619-633.
Lucas, R., "Making of A Miracle," *Econometrica* 62 (1993), 251-272.
Marshall, A., *Principles of Economics,* 8th ed (London: Macmillan, 1920).
Paniccia, I. and L. G. Carli, "Italian Industrial Districts: Evolution and Performance," mimeo http://www.scipol.unipd.it/ricerca/ConvegnoFanno/paniccia.pdf.
Romer, P., "Idea Gaps and Object Gaps in Economic Development," *Journal of Monetary Economics* 32(3) (1993), 543-73.
Saxenian, A., *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*. Cambridge: Harvard Universit Press, 1994.
Saxenian, A., "Taiwan's Hsinchu Region: Imitator and Partner for Silicon Valley," Stanford

Institute for Economic Policy Research, Discussion Paper No. 00-44 (2001).
Smarzynska, B. K., “Does Foreign Direct Investment Increase the Productivity of Domestic Firms: In Search of Spillovers through Backward Linkages,” The World Bank Policy Research Working Paper No. 2923 (2002).
Weitzman, M. L., “Recombinant Growth,” *Quarterly Journal of Economics* 113(2) (1998), 332-360.
Westphal, L. E., “Technology Strategies For Economic Development in a Fast Changing Global Economy,” *Economics of Innovation and New Technology,* 11 (4-5) (2002), 275-320.

Appendix: Description of Data and TFP Measure

The data provide information on the output and input variables that are necessary to measure total factor productivity at the firm-level: sales, employment, book value of the capital stock, and expenditures on labor and different types of intermediate inputs. A firm's output is measured as its total revenues from sales and services. This measure of output is deflated using a wholesale electronics price index. Firms use labor, capital, materials, and subcontracting services in the production. Labor is measured as the total number of workers (both production and non-production workers). The book value of a firm's capital is used to measure it capital input. This measure is constructed using a continuous inventory method where additions to capital are deflated before they are added to the measure of capital. Material inputs include raw materials, fuel, and electricity. Expenditures on raw material are deflated using a producer price index which covers both manufacturing and non-manufacturing. Expenditures on fuel and electricity are deflated using an aggregate energy price index. Because many producers hire subcontractors to perform pieces of the manufacturing process, these expenditures are included as a productive input and are deflated using the electronics price index.

The output shares of materials and subcontracting are calculated as their respective shares of total sales. The labor share of output is calculated as total wages paid to workers divided by total revenues. The capital share of output is calculated as a residual, one minus the output shares of the other inputs.

The total factor productivity (TFP) index used in this paper captures many factors that can lead to profit differences across firms, including differences in technology, age, quality of capital stock, managerial ability, scale economies, or differences in output quality. TFP is calculated for each firm in each period using a multilateral index method that was developed by Caves, Christensen and Diewert (1982), extended by Good, Naderi and Sickles (2000), and applied by Aw, Chen and Roberts (1997). To guarantee that comparisons between any two firm-year observations are transitive, the index expresses each firm's inputs and outputs as deviations from a single reference point, a hypothetical average firm for each period. This average firm produces the arithmetic mean of industry output using the arithmetic means of industry inputs. The productivity of this average firm is calculated as its output less the weighted sum of its inputs, where the weights are the industry averages of the shares of output paid to each input. The TFP measure is then linked over time by calculating the TFP of the average firm in each period relative to the TFP of the average firm in the previous period.

Letting the subscript i denote each firm and j denote various production inputs, the Good, Naderi, Sickles measure of the natural log of TFP can be written as

$$w_{it} = \left(\ln Y_{i,t} - \overline{\ln Y_t}\right) - \left(\sum_{j=1}^{n} \frac{1}{2}\left(S_{i,j,t} + \overline{S_{i,t}}\right)\left(\ln X_{i,j,t} - \overline{\ln X_{j,t}}\right)\right) +$$
$$\left(\sum_{s=2}^{t}\left(\overline{\ln Y_s} - \overline{\ln Y_{s-1}}\right)\right) - \left(\sum_{s=2}^{t}\sum_{j=1}^{n}\frac{1}{2}\left(\overline{S_{j,s}} + \overline{S_{j,s-1}}\right)\left(\overline{lnX_{j,s}} - \overline{\ln X_{j,s-1}}\right)\right)$$

where Y_{it} measures the value of output, X_{ijt} is the amount of input j, S_{ijt} is the input's share of output, and upper bars denote averages over all firms. The first line captures cross sectional differences among firms by calculating the productivity of firm i in period t relative to the average firm for the period. The second line accounts for any shifts in the distribution of TFP over time by calculating the average firm's TFP in the current period relative to the average firm's TFP in the previous period. This index measure of TFP allows for comparisons among firms within the same period as well as across periods. In addition, the index does not impose a uniform technology on all firms, which is particularly important given the wide variation of input mixes observed in the data.

The sales data for 1991 and 1996 are reported in millions of Taiwanese Dollars. Therefore, TFP can not be calculated for firms that did not have sales of at least one million Taiwanese Dollars; thus these firms are dropped from the sample. To avoid a sampling bias, the same one million dollar threshold is used to determine which firms to retain from the 1986 data. This and other data requirements result in the elimination of almost half of the total population of firms in each census year from the data.